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THE USE OF ARTIFICIAL NEURAL NETWORKS (ANN) FOR GREEN MOULDING SANDS QUALITY CONTROL

ZASTOSOWANIE SIECI NEURONOWYCH DO STEROWANIA JAKOŚCIĄ MAS FORMIERSKICH

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ABSTRACT: This article presents an attempt to use artificial neural networks (ANN) for green moulding sands quality control. Using ANN is one of the methods which helps to estimate mould sands usefulness to moulding by detecting various parameters correlations, using artificial intelligence systems.

STRESZCZENIE: W ramach niniejszego artykułu zostanie zaprezentowana próba zastosowania do sterowania jakością mas bentonitowych sieci neuronowych. Jest to metoda oceny przydatność mas za pomocą wykrywania korelacji przy użyciu systemów sztucznej inteligencji.

SŁOWA KLUCZOWE: masy syntetyczne, sztuczne sieci neuronowe, kontrola jakości

KEY WORDS: green moulding sands, artificial neural networks, quality control

1 INTRODUCTION

High competition on the international casting market and customers requirements concerning the casts quality forced foundries to keep introducing more advanced technological, economical and ecological solutions. IT solutions have recently become their integral part. They are usually related to such areas like information flow and logistics [1]. Computer systems allow to define and create processes databases, update data, to follow parameters affecting the quality and use collected data to control current quality [2, 3.

2 ARTIFICIAL NEURAL NETWORKS

One of the modern methods for production optimization is using artificial neural networks. Neural networks have been very popular during last years, because they are very handy tool. They can be used in wide range of scientific problems. This is caused by the neural networks ability to imitate complex mathematical functions. (especially their nonlinearity should be emphasized). The ability to learn and adapt has wide application in today's manufacturing industry, for example to control melting cupola processes, designing casts and gating systems, sand preparation process control, forecasting of a cast alloys properties or die casting parameters selection. The artificial neural networks are complex mathematical dependence, whose structure copies the structure and the signals processing placed in cerebral. Neural

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computation is performed by a dense mesh of computing nodes and connections. The neurons are often organized in layers and feedback connections both within the layer and toward adjacent layers are allowed. Each connection strength is expressed by a numerical value called a weight, which can be modified.

Within many of the ANN advantages the most important are:

- Ability to learn and generalize acquired knowledge. ANN make it possible to find the regularity in conditions of large number of variables of various character. That kind of dependences require applying complicated mathematical operations or they are undetectable with mathematical methods at all.
- ANN have good resistance to errors in input data and errors appearing in some weights.
- ANN make it possible to process information quickly, often in real time.

ANN belong to modern self learning systems. Constants values defining the significance of individual input data are being set, basing on the results of experiences (learning examples) and on following corrections, therefore output data (answers of the ANN) are approximate to real values. This is supervised learning, which is used most often. ANN, depending on the kind of the solved problem, can realize several kinds of tasks.

In technological processes modeling are used:

- Regression, that is approximation of unknown function of many variables, on the basis of the experimental observations results.
- Prediction, that is the expectation of the system future behaviour on the basis of sequences of values from the past with continuous adaptation of the ANN weight.
- Detecting the patterns, enabling to assemble signals showing similar features (Kohonen's ANN).

ANN can have various types of structure. The most important types are:

- Multilayer Perceptron (MLP), often used in realization of tasks connected with modelling technological processes.
- Recurrent neural networks (RNs) are models with bi-directional data flow. While a feedforward network propagates data linearly from input to output, RNs also propagate data from later processing stages to earlier stages.

ANN's learning consists in solving problem of the optimization function with many variables. Mathematically it is necessary to find such values of network weights, that the value of the average squared error from all answers of the ANN in relation to experimental observations, is the smallest.

$$E = \frac{1}{p} * \sum_{k=1}^{p} \left(\frac{1}{m} * \sum_{j=1}^{m} (d_{kj} - Y_{kj})^2 \right) \quad [4]$$

m - number of outputs,

p - number of introductions, records of experimental observations,

d - experimental values,

Y - values received from the ANN

Experimental data applied in the ANN, are usually categorized for:

- learning data, used to correct the ANN weights,
- verifying data, used to check the ANN ability to generalize by current calculation of error.

Weight corrections are executed many times during the whole learning data process. Period is one cycle of error calculation and weights modification. The end of learning ensue when average squared error begins to grow for verifying data. This is connected with the ANN possibility to over-learn, that means too excessive ANN adapting to input data, with loss of ability to the generalize.

Input data choice is an essential issue. This is connected with the input data significance for output variables. Data which are not significant should be excluded. It simplifies learning process and results analysis. Setting the outputs number one should always consider possibility of constructing several ANN with single output, which would decrease a number of the weights.

3 USING NEURAL NETWORKS IN FOUNDRY

Hülya Kaçar Durmuş, Erdoğan Özkaya, Cevdet Meri Ç [5] investigated effects of ageing conditions at various temperatures, load, sliding speed, abrasive grit diameter in aluminum alloy by using artificial neural networks. The authors showed, that the results of the experiment coincided with ANNs results.

Some interesting investigations were introduced by Mahesh B. Parappagoudar D.K. Pratihar *, G.L. Datta [6]. Quality of casting in green molding sands is influenced by green compression strength, permeability, mould hardeness, which depend on sand grain size, binder, water. Those relationships are very complicated. Back-propagation and a genetic-neural algorithms were applied to mapping relations in green sand mould system. Both kinds of ANN are able to carry out reverse mapping very effectively. There are also many Perzyk's publications [7, 8], which describes studies of using ANN in foundry.

3 INVESTIGATIONS

Attempt of the ANN module application to support decision of green moulds sands refreshing processes were undertaken. Statistica 8.0 program was used as IT tool.

At the initial stage of the investigations, choice of the suitable kind of neural networks for prognoses mould moisture based on moulds properties was made. Properties taken into account were apparent density, permeability, compression strength, wet tensile strength, tensile strength, compactability and wear resistance. As input data definite parameters in function of moisture from 1,7 to 5,51% were entered.

Neural networks automatic projector was applied in this stage. This method consists in the selection of the proper parameters of neural networks model (function of aggregation, function of activation, number of neurons) on the basis of the results achieved in consecutive experiments which used various models. The best received models are introduced in Tab. 1.

Data shown in Tab. 1, proves that the best mapping with reference to experimental results give Multi-Layer Perceptron. The Quasi-Newton method was used as learning algorithm. The Quasi-Newton methods are based on Newton's method to find the stationary point of a function, where the gradient is 0. It uses matrix reverse of the second derivatives of error functions counted in relation to following weights. The error function is used during learning and also to define error during neural networks working. The error is the sum of the squares differences among set and received output values. Next column in Tab. 1 defines the kind of a function which was applied to activate the hidden and output neural networks layer. Number of mathematical dependences (tangential, linear, logistic and exponential function) were used, among which the tangential function in the hidden layer and the linear function in output layer occur most often and together they give the best results.

Tab. 1 - The best models made by automatic projector in Statistica 8.0.

Id	ANN name	Learning Alghoritm	Terror function	Activation (hidden layer)	Activation (output layer)
1	MLP 7-19-1	BFGS 97	SOS	Tanh	Linear
2	MLP 7-12-1	BFGS 153	SOS	Tanh	Linear
3	MLP 7-18-1	BFGS 47	SOS	Tanh	Linear
4	MLP 7-22-1	BFGS 154	SOS	Logistic	Tanh
5	MLP 7-20-1	BFGS 162	SOS	Logistic	Exponential
6	MLP 7-8-1	BFGS 197	SOS	Logistic	Exponential
7	MLP 7-15-1	BFGS 92	SOS	Tanh	Sinus
8	MLP 7-12-1	BFGS 88	SOS	Exponential	Sinus
9	MLP 7-24-1	BFGS 104	SOS	Logistic	Linear
10	MLP 7-8-1	BFGS 147	SOS	Tanh	Sinus

In Tab. 2 the sensibility analysis of neural networks were introduced. The sensibility enables to distinguish important variables from those, which do not influence the results of working neural networks and they can be rejected. This is particularly useful in case when there is a need to obtain input data in a short time. The green mould sand individual paraméters sensibility specification enables rejecting the time-consuming measurements which are not necessary to the learning process.

STATISTICA Neural Network has a procedure of compensating lacks in input data. These procedures are used during the sensibility analysis. Input data are presented to the ANN many times. Every time all values of one variable (parameter), different in every repetition, are rejected and error is counted, similarly as in the standard learning process. Because of some input data being eliminated, enlargement of the error is expected. The larger the error after the rejection of one variable in relation to the primary error is; the more neural network is sensitive for the lack of this variable. If the quotient of errors amounts to 1 or is smaller than 1, removing the variable does not influence the quality of the neural network and its quality is even improved.

Data in Tab. 2 show large neural networks sensibility for all proposed input parameters among which compactability and wear resistance are featured. Tensile strength have small influence on the neural networks prediction and can be taken into consideration in case of reduction of input neurons, which leads to simplification of the neural network structure.

3 SUMMARY

Artificial Neural Networks seem to be a very interesting IT tool to support sand preparation control processes. More investigations are required to find best mapping of green mould sand systems. Finding green mould sand parameters, which are especially sensitive to active binder and wettability content should help to build neural network model, which can be used in foundries.

Tab. 2- Sensibility analysis.

	Q	P^W	R^W_C	R^W_M	R^W_P	Z	S
1.MLP 7-19-1	169,672	82,6678	9,0318	1,174124	134,5562	143,94	2188,735
2.MLP 7-12-1	359,200	171,7424	21,9157	3,986822	234,2631	1023,75	6054,136
3.MLP 7-18-1	125,989	38,7477	7,2049	1,048626	50,9379	648,55	1845,241
4.MLP 7-22-1	2884,192	185,8513	44,1385	8,792164	487,4788	1004,72	6028,084
5.MLP 7-20-1	293,737	85,0375	146,5530	1,794755	35,3758	19305,33	2587,766
6.MLP 7-8-1	244,258	155,1530	26,2979	1,811465	37,7904	107,08	1339,016
7.MLP 7-15-1	102,524	107,0288	13,8996	1,021880	106,1709	206,20	1722,746
8.MLP 7-12-1	199,951	188,6687	8,6761	2,627012	94,0629	591,72	2869,694
9.MLP 7-24-1	241,966	71,3200	32,7840	4,850252	115,2891	1063,92	3665,957
10.MLP 7-8-1	218,182	67,8113	9,4547	1,364985	81,9740	281,17	2130,053

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